MACHINE LEARNING

what it is and how to get started

Auralee Edelen
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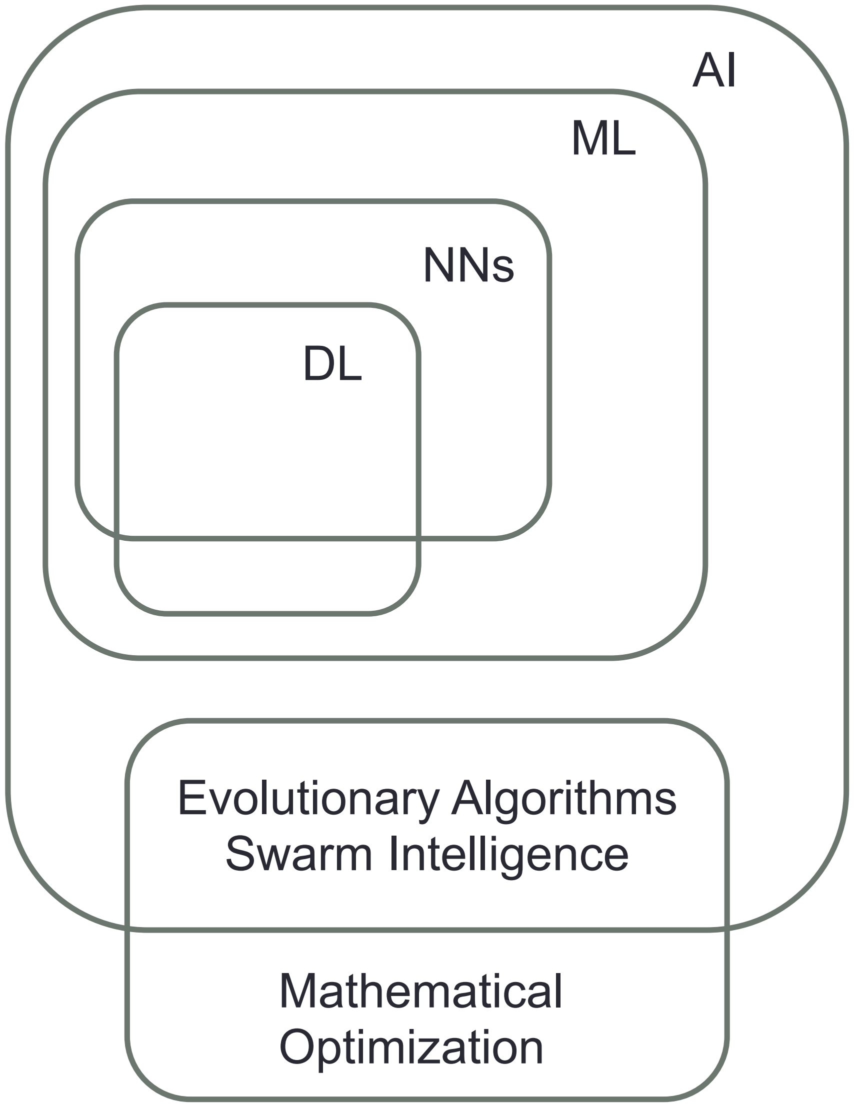
Caveats!

— 20 minutes → very high-level overview
— heavy bias toward neural networks

Field Taxonomy (as of now…)

- Artificial Intelligence (AI)
  - *Field of getting machines to exhibit aspects of human intelligence, esp. knowledge, learning, planning, reasoning, perception*
  - Narrow AI: focused on a task or similar set of tasks
  - General AI: human-equivalent or greater performance on any task
- Machine Learning (ML)
  - *Field of getting machines to complete tasks without being explicitly programmed*
  - Common tasks: Regression, Classification, Clustering, Dimensionality Reduction
- Neural Networks (NNs)
  - *A set of tools within ML that uses a many connected processing units*
  - Many kinds: feed-forward, recurrent, adversarial, self-organizing maps
  - Very popular right now (somewhere at the top of the hype cycle…)
- Deep Learning (DL)
  - *Learning hierarchical representations*
  - Right now, largely synonymous with methods based on deep (many-layered) NNs



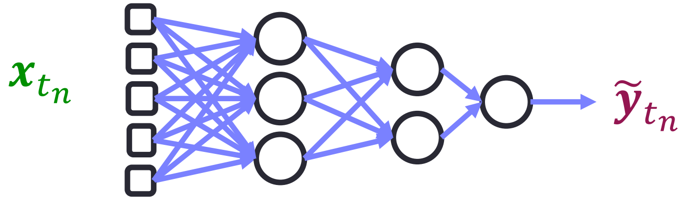
Note that these definitions are not rigid: there is a lot of fluidity in the field at the moment!

Basic Learning Paradigms

Example: Regression using a NN

Data set of **input** and **output** pairs:

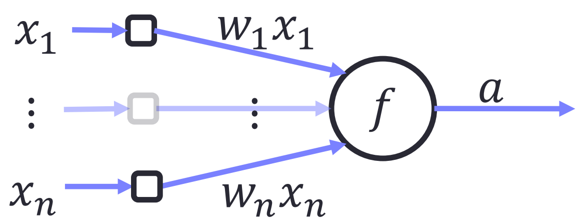
$$\left.\begin{array}{c} x_1 \\ \vdots \\ x_n \end{array}\right\} \quad \begin{array}{cc} \boldsymbol{x}_{t_1} & \boldsymbol{y}_{t_1} \\ \vdots & \vdots \\ \boldsymbol{x}_{t_n} & \boldsymbol{y}_{t_n} \end{array}$$



Want to find approximate map:

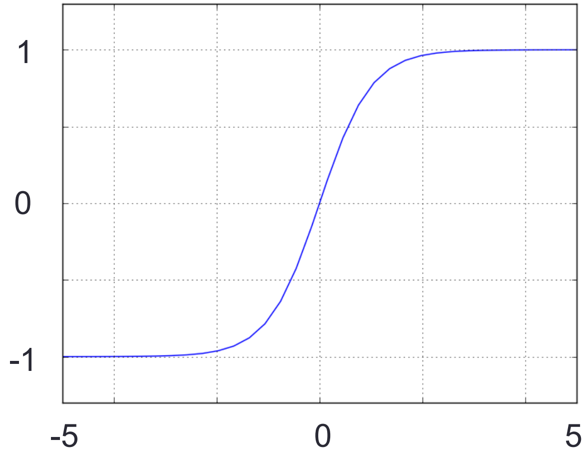
$$\boldsymbol{g}(\boldsymbol{x}) = \boldsymbol{y}$$

ANN Basic Structure

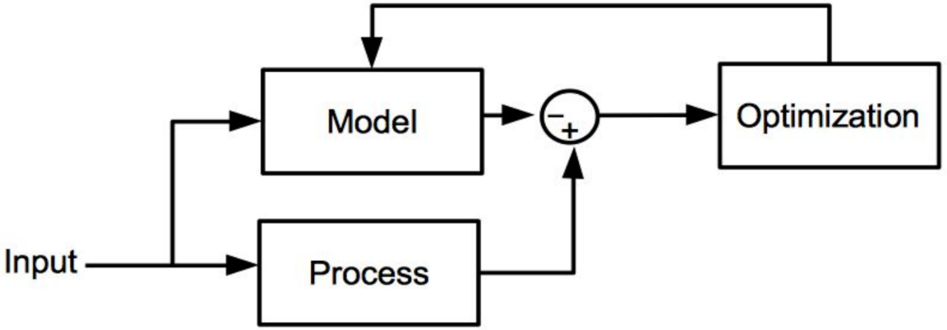


$$f\left(\sum_n w_n x_n + b\right) = a$$

e.g. $f(z) = \frac{2}{(1+e^{-2z})} - 1$



Model Learning



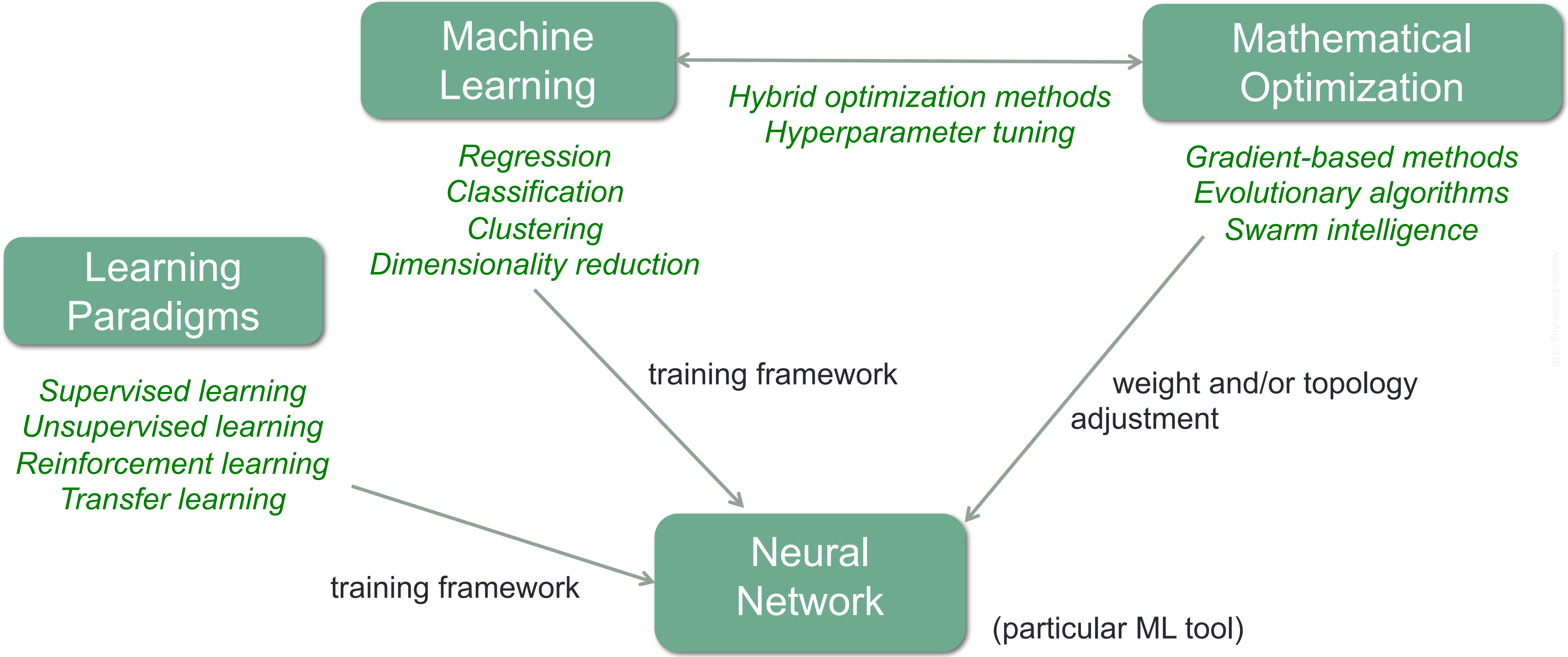
Example:

$$C(w,b) = \frac{1}{2t_n}\left[\sum_{t_n}(y_{t_n} - \tilde{y}_{t_n})^2\right]$$

$$w_k \longrightarrow w'_k = w_k - \alpha \frac{\partial C}{\partial w_k}$$

$$b_k \longrightarrow b'_k = b_k - \alpha \frac{\partial C}{\partial b_k}$$

Example of how this all fits together for NNs



ML Software and Related Libraries

- **Theano** – library for fast numerical computation (graph-based, automatic differentiation, python)
- **Tensor Flow** – library for fast numerical computation (graph-based, automatic differentiation, mostly python but some support for Java, C, Go)
- **Torch** – machine learning and scientific computing framework (Lua)
- **Scikit-learn** – library for general machine learning (python)
- **Caffe** – neural network framework (python interface, written in C++, popular in HEP, large library of pre-trained models)
- **Chainer** – neural network framework (python)
- **Lasagne** – neural network library over Theano (python)
- **Keras** – neural network library over Theano/Tensor Flow (python, also higher-level than Lasagne)
- **MATLAB** neural network toolbox

- Bare bones example of how things are structured in Theano and Lasagne

- Easy to set up mechanically

→ *much of the difficulty in using NNs comes with the training process and defining the initial problem correctly*

```python
import theano
import theano.tensor as T
import lasagne

lin = lasagne.layers.InputLayer(shape=(None, 500), input_var=input_var)

l1 = lasagne.layers.DenseLayer(lin,
    num_units = 100, nonlinearity=lasagne.nonlinearities.tanh,
    W=lasagne.init.GlorotUniform(gain=1),b=lasagne.init.Normal(std=0.001, mean=0.0))

l2 = lasagne.layers.DenseLayer(l1,
    num_units = 70, nonlinearity=lasagne.nonlinearities.tanh,
    W=lasagne.init.GlorotUniform(gain=1),b=lasagne.init.Normal(std=0.001, mean=0.0))

l3 = lasagne.layers.DenseLayer(l2,
    num_units = 10, nonlinearity=lasagne.nonlinearities.tanh,
    W=lasagne.init.GlorotUniform(gain=1),b=lasagne.init.Normal(std=0.001, mean=0.0))

out = lasagne.layers.DenseLayer(l3,
    num_units = 1, nonlinearity=lasagne.nonlinearities.linear,
    W=lasagne.init.GlorotUniform(gain=1),b=lasagne.init.Normal(std=0.001, mean=0.0))

input_var = T.matrix('inputs', dtype='float32')
target_var = T.matrix('targets',dtype='float32')

prediction = lasagne.layers.get_output(out)

loss = lasagne.objectives.squared_error(prediction, target_var)
params = lasagne.layers.get_all_params(out, trainable=True)
updates = lasagne.updates.adam(loss, params, learning_rate=0.0001)
train_fn = theano.function([input_var,target_var],[loss,prediction])

#would then use the following to do one training update, where "inputs" and "targets"
#are your training data:
trn_loss,trn_pred = train_fn(inputs,targets)
```

Questions?

Backpropagation

Vectorized notation: $a_j = f\left(\sum_k w_{jk} x_k + b_j\right) \rightarrow f(wx+b)$

Layer-by layer: $a^l = f\left(w^l a^{l-1} + b^l\right) = f(z^l)$

a_j j^{th} node activation

b_j j^{th} node bias

w_{jk} j^{th} node in layer l, k^{th} node in $l-1$

f applied element-wise

$$\delta_j^l \equiv \frac{\partial C}{\partial z_j^l}$$

$$\delta_j^{N_l} = \frac{\partial C}{\partial a_j^{N_l}} f'(z_j^{N_l}) \rightarrow \delta^{N_l} = \nabla_a C \odot f'(z^{N_l})$$

$$\delta_j^l = \sum_k \frac{\partial C}{\partial z_k^{l+1}} \frac{\partial z_k^{l+1}}{\partial z_j^l} = \sum_k \delta_k^{l+1} \frac{\partial z_k^{l+1}}{\partial z_j^l}$$

$$= \sum_k w_{kj}^{l+1} \delta_k^{l+1} f'(z_j^l)$$

$$z_k^{l+1} = \sum_j w_{kj}^{l+1} a_j^l + b_k^{l+1}$$
$$= \sum_j w_{kj}^{l+1} f(z_j^l) + b_k^{l+1}$$

$$\frac{\partial z_k^{l+1}}{\partial z_j^l} = w_{kj}^{l+1} f'(z_j^l)$$

For each training instance:

1. Forward Pass:

For $l = 1, 2, 3 \ldots N_l$

$z^l = w^l a^{l-1} + b$

$a^l = f(z^l)$

2. 'Error':

$\delta^{N_l} = \nabla_a C \odot f'(z^{N_l})$

3. Backward Pass:

For $l = N_l - 1, N_l - 2, \ldots 1$

$\delta^l = w^{l+1} \delta^{l+1} \odot f'(z^l)$

4. Final Derivatives:

$$\frac{\partial C}{\partial w_{jk}^l} = a_k^{l-1} \delta_j^l \qquad \frac{\partial C}{\partial b_j^l} = \delta_j^l$$